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# Mindless reading revisited: An analysis based on the SWIFT model of eye-movement control

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## ABSTRACT

In this article, we revisit the *mindless reading paradigm* from the perspective of computational modeling. In the standard version of the paradigm, participants read sentences in both their normal version as well as the transformed (or mindless) version where each letter is replaced with a *z*. *z*-String scanning shares the oculomotor requirements with reading but none of the higher-level lexical and semantic processes. Here we use the *z*-string scanning task to validate the SWIFT model of saccade generation [Engbert, R., Nuthmann, A., Richter, E., & Kliegl, R. (2005). SWIFT: A dynamical model of saccade generation during reading. *Psychological Review*, 112(4), 777–813] as an example for an advanced theory of eye-movement control in reading. We test the central assumption of spatially distributed processing across an attentional gradient proposed by the SWIFT model. Key experimental results like prolonged average fixation durations in *z*-string scanning compared to normal reading and the existence of a string-length effect on fixation durations and probabilities were reproduced by the model, which lends support to the model's assumptions on visual processing. Moreover, simulation results for patterns of regressive saccades in *z*-string scanning confirm SWIFT's concept of activation field dynamics for the selection of saccade targets.

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## 1. Introduction

Reading is a demanding activity requiring the coordination of many different stages of information processing. Due to visual acuity limitations, in reading and other visual–cognitive tasks the eyes generate short and rapid movements, called *saccades*, at an average rate of 3–4 per second. During *fixations*, defined as the periods between saccades, the eyes remain relatively motionless and visual information processing is achieved. A typical reading fixation lasts for about 200–250 ms while saccades move the eyes forward for about 6–7 character spaces. During reading, word processing is the main task, but it is subject to the restrictions arising from the oculomotor system that moves the eyes. Therefore, a complete theory of any visual–cognitive task involving eye movements requires one to understand how the visual and cognitive processes and oculomotor control interact (Rayner, 1998).

### 1.1. Models of eye-movement control in reading

As for reading, current computational models of eye-movement control in reading provide theoretical frameworks for understand-

ing how word identification, visual processing, attention, and oculomotor control jointly determine when and where the eyes move during reading. Theoretical models of eye-movement control during reading can be contrasted as primary cognitive versus oculomotor models (cf., Rayner, Sereno, & Raney, 1996; Starr & Rayner, 2001). Cognitive models are based on the assumption that ongoing cognitive processing drives eye movements during reading, while oculomotor models hypothesize that eye movements are mainly controlled by low-level oculomotor or visuomotor processes.

Cognitive models assume that eye movements are driven primarily by lexical processing. They can be categorized according to how they conceptualize the allocation of visual attention. For models based on *sequential attention shifts* (SAS models), the serial allocation of visual attention from one word to the next is the key mechanism driving eye movements. The currently most advanced SAS model is E-Z Reader (Pollatsek, Reichle, & Rayner, 2006; Reichle, Pollatsek, Fisher, & Rayner, 1998; Reichle, Rayner, & Pollatsek, 2003). In E-Z Reader, word processing is strictly serial while saccades can be programmed in parallel. Other models, first and foremost the SWIFT model (Engbert, Longtin, & Kliegl, 2002; Engbert, Nuthmann, Richter, & Kliegl, 2005), assume *guidance by attentional gradients* (GAG). Specifically, GAG models assume that attention is distributed continuously as a gradient. As a consequence, several words are processed in parallel. Another model arguing for parallel processing of foveal and parafoveal words is Glenmore, an interactive activation model (Reilly & Radach, 2006).

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The most prominent example of an oculomotor model is O'Regan's strategy-tactics theory (O'Regan, 1990, 1992; O'Regan & Lévy-Schoen, 1987). According to this theory, the eyes' initial landing position in a word largely determines how long to fixate on a word and where to go next. It is proposed that readers adopt a global strategy (e.g., careful or risky reading) that coarsely influences fixations and saccades. It is also proposed that readers implement local, within-word tactics that are based on lower level, nonlexical information. Work by McConkie and colleagues on the preferred viewing position (McConkie, Kerr, Reddix, & Zola, 1988) and optimal viewing position (McConkie, Kerr, Reddix, Zola, & Jacobs, 1989) in reading can also be seen in this oculomotor tradition. Taking up on the work by McConkie et al. (1988), Reilly and O'Regan (1998) performed computer simulations to test different word-targeting strategies in reading on the basis of low-level heuristics. A more recent primary oculomotor model was suggested by Yang and McConkie (2001, 2004), see Yang (2006) for an implementation. The key assumption of their competition-interaction theory is that the timing of saccades is largely independent of lexical processing. However, processing difficulty can inhibit the oculomotor system from initiating a saccade program. Another recent primary oculomotor model is SERIF<sup>1</sup> (McDonald, Carpenter, & Shillcock, 2005), aiming at modeling the joint influence of anatomical, oculomotor, and perceptual-visual factors on eye movement control in reading. In particular, the SERIF model postulates that vertical foveal splitting is a fundamental constraint on reading, and saccade latencies are simulated as a race between two rise-to-threshold saccadic decision units, located in the cerebral hemispheres.

Generally, any successful computational model will likely have to accommodate both cognitive-attentional and visuomotor aspects of eye-movement control (Radach & Kennedy, 2004). Therefore, labeling models as either oculomotor or cognitive is more a question of emphasis than binary classification. For example, in the E-Z Reader model, saccades are triggered by the completion of a first stage of lexical access and thus by a cognitive event. In the SWIFT model, saccade programs are triggered by a stochastic process, which is modulated by local activation related to word difficulty. While this difference in model architecture is important for the mathematical implementation of the underlying stochastic processes, fixation duration is controlled by ongoing cognition in both models. Furthermore, in the SWIFT model the decision about where to move next is intimately tied to lexical processing. In contrast, in a serial model like E-Z Reader words are processed one at a time implying that the next word is the default saccade target. For a review and comparison of computational models see Reichle et al. (2003).

## 1.2. Mindless reading

As far as empirical research on eye-movement control in reading is concerned, one of the currently most relevant issues is to determine the relative influences of low-level visuomotor factors and higher-level cognitive factors on eye-movement control (Starr & Rayner, 2001). One approach is to simultaneously test the influence of a set of low-level and higher-level predictors on, for example, fixation durations, using repeated measures multiple regression analyses (Kliegl, Nuthmann, & Engbert, 2006) or linear mixed-effects models (Kliegl, 2007). Within this framework, word length, word frequency and, predictability are the most important word characteristics currently investigated. Word length is the central low-level visuomotor variable. A key finding is that the longer the word, the longer the eyes remain fixated on that word (e.g., Kliegl et al., 2006). Furthermore, fixation durations systematically vary with within-word fixation position, and launch site dis-

tance (e.g., Vitu, McConkie, Kerr, & O'Regan, 2001). Two extensively investigated linguistic variables are word frequency and predictability. Word frequency denotes the frequency of occurrence of a given word in printed text of a given language, roughly reflecting the lexical processing difficulty of the word. Predictability is defined as the probability of guessing a word from the preceding context. Fixation durations decrease with increasing word frequency and predictability (e.g., Kliegl et al., 2006).

Another attempt to investigate the issue of the relative influences of oculomotor versus cognitive processes originates in experimental research. Vitu, O'Regan, Inhoff, and Topolski (1995) introduced the so-called mindless reading paradigm (see also Inhoff, Topolski, Vitu, & O'Regan, 1993) which motivated our study. The basic idea is to create a scanning task which shares oculomotor requirements with reading, but none of the higher-level lexical, semantic, or syntactic processes present in normal reading. Typically, all letters of the text are replaced by z's. Participants read sentences in their normal version (e.g., *Reading is a complex skill.*) and scan the transformed (or mindless) z-version (e.g., *Zzzzzzzz zz z zzzzzzzz zzzzzz.*). Participants are instructed to scan the z-strings as if they were reading. Obviously, z-strings have no predictability, and the notion of word and/or string frequency becomes obsolete. Consequently, the length of the string is a key variable for eye-movement control in the z-string scanning task. Originally, the mindless reading paradigm was based on the following logic: In both conditions, eye movements will be influenced by roughly the same visual and oculomotor factors. If only low-level visuomotor variables and the properties of the oculomotor system determine when and where readers move their eyes, then one would predict that the eye movements of readers who are reading normally (i.e., reading with full comprehension) will look very similar to those of readers who are engaged in a mindless reading task like z-string scanning. In the latter case, the cognitive processes supporting comprehension are absent. Thus, if cognitive processes are driving eye-movements in reading, then one might predict that eye-movement patterns of readers who are scanning z-strings will look different from those of readers who are reading words. To a certain degree, the logic underlying this approach is an idealization. We cannot rule out with certainty that participants do not introduce some other component that is typically not part of normal reading.

Three experimental studies report that eye movements do indicate differences between z-string scanning and normal reading (Nuthmann, Engbert, & Kliegl, 2007; Rayner & Fischer, 1996; Vitu et al., 1995). The most striking finding from the empirical studies is that fixation durations are prolonged in scanning sentences consisting of z-strings as compared to reading of normal sentences (see also Drieghe, Brysbaert, & Desmet, 2005; Liversedge et al., 2004). This is counterintuitive: As there is nothing meaningful to process, one would expect fixation durations to actually be shorter in z-string scanning. Fixation durations on z-strings are further sensitive to the length of the string, with longer fixation durations on longer strings. In addition, there are fewer regressive, i.e., left-directed inter-word and intra-word saccades. As far as forward or progressive saccades are concerned, the proportion of short as well as very long saccades is higher when scanning z-strings than when reading normal sentences. Landing position distributions are very similar in both conditions.

In sum, differences between normal reading and z-string scanning do exist. Looking at the two original studies, interpretation of the observed differences poses an unsolved problem. Observed differences were interpreted either in terms of an "astonishing resemblance" (Vitu et al., 1995, p. 361) or as fundamental differences (Rayner & Fischer, 1996). Consequently, the differences were interpreted as evidence for a minor (Vitu et al., 1995) or major (Rayner & Fischer, 1996) contribution of higher-level language-re-

<sup>1</sup> Stochastic model of Eye movements in Reading Incorporating foveal Splitting.

lated processes to eye-movement control in reading. However, these interpretations may have been influenced by the theoretical position advocated.

In this study, our aim is to take a different approach to this issue rather than to pass judgement on previous interpretations. We utilize the z-string scanning task to approach the issue of model generalizability. What is unique about reading is that it engages both vision and language. However, humans did not specially adapt to reading. As a working assumption for a general model of eye-movement control, we therefore propose that there is a common basic architecture which is modulated by task-specific mechanisms. Consequently, models of eye-movement control in reading must have the potential for generalization to nonreading tasks like visual search (e.g., the sequential search task developed by Trukenbrod & Engbert, 2007) or scene perception. Modeling z-string scanning, a simple task in a well-structured visual layout solely operating in the horizontal dimension, can be considered to be a first step in this direction. Of course, the presupposition here is that z-string scanning indeed constitutes a valid oculomotor control condition to reading, an issue we will discuss in depth in Section 4. With the present work, we aimed at modeling z-string scanning data with the SWIFT model of saccade generation (Engbert et al., 2005). Put simply, if the SWIFT model has the potential for generalization to non-reading tasks, it should not break down when we block out the language-related influences in order to simulate z-string scanning. Note that we perform a rigorous test as we do not change the basic architecture of the model. In particular, the present simulations will test the model's assumptions on visual processing, saccade generation, and the concept of an evolving activation field for saccade planning.

### 1.3. The SWIFT model

SWIFT<sup>2</sup> represents a dynamical systems approach to eye-movement control in reading, based on the concept of spatially distributed, or parallel processing of words. One major motivation for developing SWIFT was to propose one common mechanism to describe all types of saccades observed in reading experiments, i.e., forward saccades, word skippings, refixations, and regressions. Additionally, as a key principle derived from neurophysiological work (Findlay & Walker, 1999), “when” and “where” pathways of saccade preparation are separated in SWIFT.

#### 1.3.1. Dynamic field of activations

The notion of a spatially distributed field of activations in SWIFT is related to recent advances in the dynamic field theory of movement preparation by Erlhagen and Schöner (2002). Generally, SWIFT represents a simplified version of the dynamic field theory, where a one-dimensional field of activations for words serves as a dynamic saliency map from which saccade-targeting probabilities are computed.

#### 1.3.2. Word Difficulty

Activation is built up to a maximum and later decreases again. The maximum activation  $L_n$  of word  $n$  is related to the word's processing difficulty, which is estimated from word frequency, that is,

$$L_n = \alpha \left( 1 + \beta \frac{\log f_n}{F} \right), \quad (1)$$

where  $\alpha$  is the intercept value of the lexical access time. The intercept is modulated by the natural logarithm of word frequency,  $f_n$ , with slope parameter  $\beta$  and scaling constant  $F$ .

#### 1.3.3. Processing rate

SWIFT's concept of a processing gradient combines what is known as the perceptual span with the notion of parallel processing of words in a sentence. First, the region from which useful visual information can be encoded is called the visual span. If only visual acuity limitations contributed to the span, it should extend symmetrically to the left and right of the current fixation position. In reading, however, we observe a left–right asymmetry due to the direction of the writing system<sup>3</sup>, supporting the concept of an attention-based perceptual span (e.g., Henderson & Ferreira, 1990). Operationally, the perceptual span refers to the region of visual field that influences eye movements and fixation times in reading (McConkie & Rayner, 1975). Second, there is an accumulating body of empirical evidence suggesting that word processing in reading is spatially distributed (see Kliegl et al., 2006, for discussion). Therefore, in SWIFT we assume that processing is distributed across all words within the current perceptual span. The implementation of this theoretical concept is called processing gradient. We formulate that the processing rate is a function of the eccentricity, i.e., distance, of a word from the current fixation position. The distance between letter  $j$  of word  $n$  and the current fixation position  $k(t)$  is given by the eccentricity

$$\epsilon_{nj}(t) = x_{nj} - k(t), \quad (2)$$

where  $x_{nj}$  denotes the position of letter  $j$  of word  $n$ . Further, the relationship between processing rate and eccentricity is implemented as an asymmetric Gaussian function, i.e.,

$$\lambda(\epsilon) = \lambda_0 \exp \left( -\frac{\epsilon^2}{2\sigma^2} \right) \quad \text{with} \quad \sigma = \begin{cases} \sigma_L & \text{if } \epsilon < 0 \\ \sigma_R & \text{if } \epsilon \geq 0 \end{cases}, \quad (3)$$

where  $\sigma_L$  and  $\sigma_R$  represent the extension of the processing rate to the left and to the right of fixation, respectively (see Fig. 1). Taken together, the standard deviations of the processing gradient reflect both visual and attentional influences. The normalization constant  $\lambda_0$  fixes the total processing rate at a constant value of 1 (for details see Engbert et al., 2005).

Finally, the processing rate for a given word  $n$  at time  $t$  is calculated as

$$\lambda_n(t) = (M_n)^{-\eta} \sum_{j=1}^{M_n} \lambda(\epsilon_{nj}(t)), \quad (4)$$

where  $M_n$  is the length of word  $n$  in letters, and  $\eta$  is a word length exponent which can vary between 0 and 1. In case of  $\eta = 0$  (processing rate of a word is the sum of the rates of all its letters), processing speed is biased towards long words.  $\eta = 1$  (processing rate is mean of all letters) translates into a processing advantage of short words (for details see Engbert et al., 2005). For normal reading, simulations yielded an intermediate value between these two extremes (Table 1).

#### 1.3.4. Temporal evolution of the field of activations

The dynamics of the activation field for a sentence with  $N$  words are governed by a  $N$ -dimensional set of coupled ordinary differential equations,

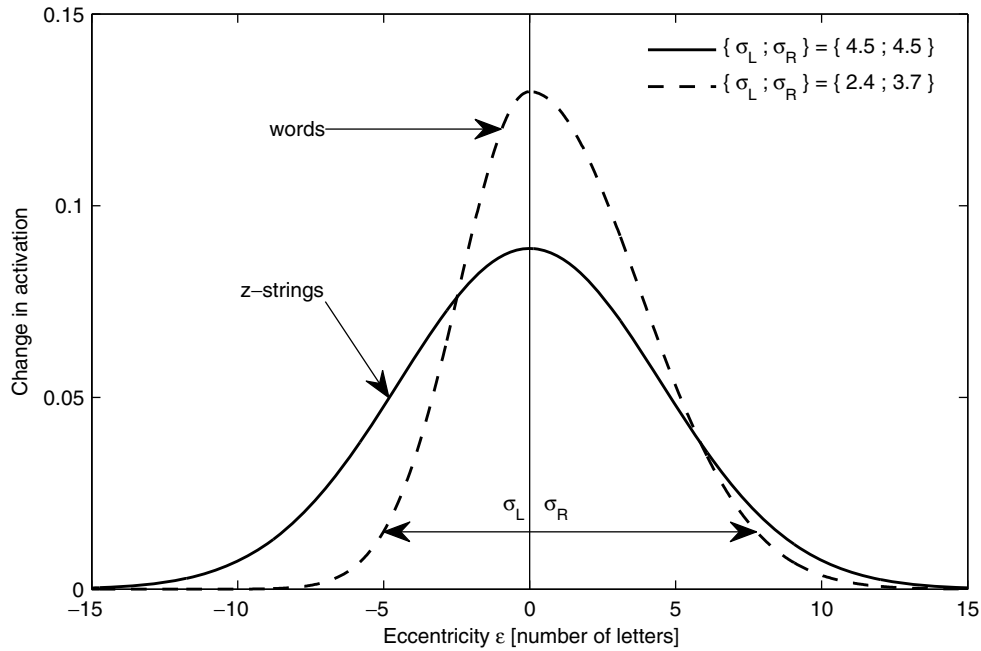
$$\frac{da_n(t)}{dt} = F_n(t)A_n(t) - \omega, \quad (5)$$

where  $a_n(t)$  represents word  $n$ 's activation value.  $A_n(t)$  is the processing rate, and  $F_n(t)$  is a preprocessing factor, which introduces a fast buildup of activation in an early processing stage. In addition, SWIFT assumes a decay process of activation which can be interpreted as a memory leakage. It is implemented as a global

<sup>2</sup> SWIFT is an acronym for autonomous Saccade generation With Inhibition by Foveal Targets.

<sup>3</sup> In Western languages, the span extends further to the right than to the left, while the opposite is true for Hebrew (Pollatsek, Bolozky, Well, & Rayner, 1981).





**Fig. 1.** Processing rate is implemented as a normalized asymmetric Gaussian distribution with free parameters  $\sigma_L$  and  $\sigma_R$  to the left and right of the fixation point ( $\epsilon = 0$ ) respectively. Solid and broken lines roughly correspond to parameter estimates for z-strings versus words.

parameter  $\omega$  inducing a slow decrease of activations of words with a constant rate [cf., Eq. (5)].

### 1.3.5. Saccade target selection

There is consensus on the issue that reading saccades have a functional target (cf., Radach & Kennedy, 2004, but see Vitu, 2003) which would be a word, and, at least for inter-word saccades, the center of that word (McConkie et al., 1988). We assume that readers employ similar saccade targeting strategies in reading and z-string scanning, a claim which we think is supported by the indistinguishable word-length-contingent landing position distributions in both conditions (Nuthmann et al., 2007). In SWIFT, saccade target selection is thus object-based (with an object being a word or string). The word/string with the currently highest activation has the highest probability of being selected as the target for the next saccade. The probability  $\pi(n, t)$  to select word  $n$  as target for the next saccade at time  $t$  is determined by its relative activation

$$\pi(n, t) = \frac{a_n^\gamma(t)}{\sum_{j=1}^N a_j^\gamma(t)}, \quad (6)$$

where the exponent  $\gamma$  is a measure for the stochasticity in target selection. Simulations of normal reading data yielded  $\gamma = 1$  (cf., Table 1), i.e., target selection probability is proportional to the relative lexical activation of words (Engbert et al., 2005). The target is selected at the end of the labile stage of saccade programming (see below).

### 1.3.6. Oculomotor errors

After target selection, the saccade is directed to the center of the word, or its *optimal viewing position* (OVP, cf., Section 3.2.6). Consequently, the *intended* saccade amplitude  $A$  is the distance between the current fixation position and the optimal viewing position of the next target word. The *realized* saccade length  $l$ , however, is subject to systematic and random oculomotor error (Engbert & Nuthmann, 2008; McConkie et al., 1988). The realized saccade length  $l$  is thus calculated as the sum of the intended saccade amplitude  $A$  and two error terms,

$$l = A + l_{\text{SYS}} + l_G, \quad (7)$$

where  $l_{\text{SYS}}$  is the systematic error component and  $l_G$  is Gaussian-distributed random error with zero mean. If the intended saccade amplitude  $A$  differs from an optimal saccade amplitude  $A_0$  (the optimal center-based launch site distance), the eyes will undershoot the word center for  $A > A_0$  and overshoot the word center for  $A < A_0$ . In a linear approximation of this effect, the systematic error component can be expressed as

$$l_{\text{SYS}} = \delta_{\text{SYS}}(A_0 - |A|), \quad (8)$$

where  $\delta_{\text{SYS}}$  represents the strength of the systematic error component. In addition, the inherent motor noise in saccade execution is simulated by adding Gaussian-distributed random error with zero mean. This random component of oculomotor error increases as movement amplitude increases. Therefore, we approximate the standard deviation of the random error by the linear relation

$$\sigma_G = \delta_0 + \delta_1 |A|. \quad (9)$$

To summarize, Eq. (7)–(9) determine where a saccade lands when aimed at a word of a certain length and eccentricity. As a result, we will observe launch-site-contingent landing position distributions (Fig. 6). Parameters  $\delta_{\text{SYS}}$ ,  $A_0$ ,  $\delta_0$ , and  $\delta_1$  can be estimated from empirical data (Table 2).

### 1.3.7. Mislocated fixations

Oculomotor errors have the eyes undershoot or overshoot the center of words. However, these errors can also lead to instances where the eyes don't even land on the intended target word, but instead on a word to the left or right of it. This is what we call a *mislocated fixation* (cf., Engbert & Nuthmann, 2008; McConkie et al., 1988). With recent work, we computationally linked these mislocated fixations to the Inverted-Optimal Viewing Position (IOVP) effect for fixation durations (Engbert, Nuthmann, & Kliegl, 2007; Nuthmann, Engbert, & Kliegl, 2005; Nuthmann et al., 2007), suggesting that the eyes will respond to mislocated fixations with the start of a new, potentially error-correcting saccade program. Because mislocated fixations occur most frequently at word boundaries, the immediate start of a saccade program

**Table 1**

Model parameters for z-string scanning versus normal reading.

	Parameter	Symbol	z-Strings	Error <sup>a</sup>	Words <sup>b</sup>	Error <sup>c</sup>	Range <sup>d</sup>	Equation
Lexical parameters	Frequency, intercept	$\alpha$	65.0	0.3	63.5	2.0	10–150	
	Frequency, slope	$\beta$	–	–	–0.20	0.03	–	
	Predictability	$\theta$	–	–	0.11	0.09	–	
Visual processing	Visual span, right	$\sigma_R$	4.50	0.03	3.74	0.08	1–7	Eq. (3)
	Visual span, left	$\sigma_L$	4.48	0.001	2.41	0.15	0–7	Eq. (3)
	Word length exponent	$\eta$	0.93	0.007	0.448	0.035	0–1	Eq. (4)
	Preprocessing factor	$f$	220	8.5	70.2	20.6	1–1000	Eq. (5)
	Global decay	$\omega$	0.055	0.001	0.01		0–0.10	Eq. (5)
	Processing noise	$\varphi$	2		2			
Saccade timing	Random timing (ms)	$t_{sac}$	182.6	2.1	179.0	3.6	150–300	Eq. (10)
	Inhibition factor	$h$	4.4	0.09	2.62	0.15	0–10	Eq. (10)
	Time delay	$\tau$	232.9	5.0	375.7	30.0	2–300	Eq. (10)
	Target selection weight	$\gamma$	1		1			Eq. (6)
Saccade programming	Labile stage (ms)	$\tau_{lab}$	143.1	0.6	108.0	1.5	50–150	
	Nonlabile stage (ms)	$\tau_{nl}^0$	20.5	1.0	6.1	2.7	5–50	
	Latency modulation	$\kappa_0$	78.1	3.3	105.2	2.7	0–200	
	Latency modulation	$\kappa_1$	0.1		0.1			

<sup>a</sup> Error estimates are standard deviations of parameter estimates over generations of the genetic algorithm.<sup>b</sup> Parameter estimates for normal reading are taken from Engbert et al. (2005).<sup>c</sup> Error values for normal reading are taken from Engbert et al. (2005).<sup>d</sup> The range column lists parameter boundaries used in fitting of z-strings.

generates the typical inverted *u*-shaped pattern for fixation durations as a function of landing position: Fixation durations are longer close to word center as compared to word edges (Vitu et al., 2001). To validate this IOVP model with the SWIFT model, the following principle was implemented: In response to a mislocated fixation, a new saccade program will be started immediately if there is currently no labile saccade program active (Engbert et al., 2005, 2007). This correction mechanism for mislocated fixations was able to reproduce the IOVP effect for single fixation durations (Engbert et al., 2005, Fig. 15). However, to reproduce the IOVP effect for the first of multiple fixations as well as the fixation duration trade-off effect for two-fixation cases, the model was furnished with an additional saccade latency modulation principle (for details see Engbert et al., 2005).

### 1.3.8. Modulation of fixation durations by foveal inhibition

As for the temporal aspect of saccade generation, reflected by saccade latencies and/or fixation durations, SWIFT assumes stochastic intervals between two subsequent decisions to initiate a new saccade program (cf., Yang & McConkie, 2001). This autonomous timing is realised with a mean value  $t_{sac}$  drawn from a gamma distribution. Importantly, the stochastic process can be modulated by foveal inhibition.<sup>4</sup> As a result, dependent on the activation of the fixated word at time  $t$ , and hence dependent on ongoing processing of the word, the initiation of a new saccade program can be inhibited. The program for the next saccade  $i + 1$  is started, if

$$t > t_i + \Delta t_{i+1} + h[a_k(t)]_\tau, \quad (10)$$

where  $h$  represents the strength of the foveal inhibition process.

### 1.3.9. Saccade programming

In SWIFT, saccades can be programmed in parallel. The implementation was inspired by work with the double-step paradigm suggesting that saccade programming is completed in two stages: an initial, labile stage that is subject to cancellation, and an ensuing, non-labile stage in which the program can no longer be cancelled (Becker & Jürgens, 1979). Thus, if SWIFT's autonomous timer initiates a second saccade program during the non-labile

stage of the first one, both will be executed. Note that SWIFT's autonomous saccade timer is overruled when a new saccade program is initiated in response to a mislocated fixation. For further details of the mathematical formulation of SWIFT see Engbert et al. (2005).

### 1.4. SWIFT predictions for z-string scanning

The focus of the present paper is on testing whether the SWIFT model generalizes from reading to scanning behavior. In the following, we discuss how changes of SWIFT parameter values might explain key experimental observations in the z-string scanning paradigm. Can the model reproduce the globally prolonged fixation durations (Section 1.4.1) as well as the string length effect (Section 1.4.2) obtained in the z-string scanning task? Is the SWIFT concept of an evolving field of activations of words and/or strings adequate? The latter question can be addressed by modeling regression behavior in z-string scanning (Section 1.4.3).

#### 1.4.1. Prolonged fixation durations

Average fixation durations in SWIFT are controlled by two different processes. First, the mean value  $t_{sac}$  of the stochastic process underlying the initiation of a new saccade program determines the average fixation duration. When reading meaningless material, the mean value  $t_{sac}$  could be increased, which automatically yields longer fixation durations. It is reasonable to assume that semantic processes and expectations formed about the next word exert a pull to drive the eyes forward in reading. Therefore, a higher mean value  $t_{sac}$  for scanning meaningless material appears psychologically plausible.

Second, fixation durations are modulated by foveal inhibition. The strength of this inhibitory process is determined by the activation of the currently fixated word or string. Because the temporal evolution of the activation field is the key cognitive principle for movement planning in SWIFT, foveal inhibition is the cognitive principle underlying the control of fixation durations in the model. In earlier work (Richter, Engbert, & Kliegl, 2006), it was shown that the impact of foveal inhibition on fixation durations is limited, even for arbitrary large values of the parameter  $h$  which determines the strength of foveal inhibition. The reason can be seen from the structure of Eq. 10: As soon as word  $k$  is fixated, the acti-

<sup>4</sup> In its current implementation, foveal inhibition modulates fixation durations with a temporal delay (Engbert et al., 2005), where  $[a_k(t)]_\tau = \frac{1}{\tau} \int_{t-\tau}^t a_k(t') dt'$ .

**Table 2**

Oculomotor error parameters for scanning of z-strings versus reading of words.

Systematic error					Random error			
Saccade type	Slope ( $\delta_{\text{sys}}$ )		$A_0^a$		$\delta_0$		$\delta_1$	
	z-Strings	Words	z-Strings	Words	z-Strings	Words	z-Strings	Words
Forward saccade	0.37	0.41	4.45	5.4	0.65	0.87	0.127	0.084
Forward refixation	0.46	0.49	5.41	5.7	0.65	0.87	0.127	0.084
Regressive refixation	−0.46	−0.5	5.41	4.3	0.65	0.87	0.127	0.084
Regression	0.0	−0.15	0.0	10.0	0.65	0.87	0.127	0.084

<sup>a</sup> Optimal center-based launch site distance.

vation  $a_k(t)$  rapidly approaches zero, because the processing rate is at its maximum on the fixated word. As soon as  $a_k(t)$  reaches a value of zero, however, even arbitrary large values of  $h$  can no longer inhibit the upcoming start of the next saccade program (for a mathematical analysis see Richter et al., 2006). Thus, as far as inflated fixation durations in z-string scanning are concerned, the dynamics of word-based activations might be more important than the specific value of the inhibition factor  $h$ .

An alternative mechanism in SWIFT to explain increased average fixation durations in z-string scanning is related to the size of the perceptual span. The size of the span can be modulated by foveal load (e.g., Henderson & Ferreira, 1990). For scanning of meaningless material, we would expect decreased foveal load and thus a broadening of the perceptual span. Because of the normalization of the total amount of processing, Eq. (3), a larger perceptual span will lead to a decreased processing rate for each single letter, which generates more simultaneous activation over the set of z-strings compared to words, because build-up and decline of activation is slowed down. Note that more global activation causes more inhibition, which leads to delayed saccade initiation and thus longer average fixation durations. As a final prediction, simulations could also yield a broader span combined with slower saccade timing.

#### 1.4.2. Effects of string length

In the SWIFT model, processing rates for words are computed in two steps. First, letter-based processing rates are obtained from the asymmetric Gaussian function, Eq. (3). Second, the processing rate for words is calculated from a weighted sum of the letter-based rates. The word-length exponent determines the influence of word length, Eq. (4). Therefore, three parameters (extensions of the processing span to the left and right, and the word length exponent) regulate effects of word length on various measures of eye-movement behavior. For the present simulations of z-string scanning, we do not modify these assumptions. Therefore, we expect to observe string length effects in the simulated data. The question arises, however, whether the strength of the simulated effects is psychologically plausible. From this perspective, modeling string-length effects in z-string scanning is an important test of the SWIFT model's assumptions on visual processing, in particular, the shape and size of the processing span and the computation of processing rates.

#### 1.4.3. Reduced regression probability

Experimental data suggest a considerably reduced regression probability in z-string scanning. In the SWIFT model, regressions are triggered by incomplete processing of words. Given SWIFT's saccade targeting mechanism there are basically two factors influencing the model's regression behavior, (1) the extension of the perceptual span to the left of the current fixation position ( $\sigma_L$ , Eq. 3) and (2) the global decay parameter  $\omega$  (cf., Eq. 5). A reduced regression probability could be obtained by a faster decay of activation for z-strings compared with words. Consequently, a greater

global decay parameter  $\omega$  could adjust the regression pattern to the values observed in scanning. Another possibility is that the extension of the processing span to the left,  $\sigma_L$ , is larger compared to the value for normal reading. If  $\sigma_L$  is small, even a slight overshoot of the word's or z-string's center induces a considerably slowed processing rate, which will often require a later regression. Thus, a more symmetric processing span with a larger  $\sigma_L$  will be most likely for z-scanning. Both model parameters,  $\sigma_L$  and  $\omega$ , will interact in the control of regression probability, which makes it difficult to predict their numerical values for z-string scanning.

## 2. Experiment

To test these predictions, a simulation study with the SWIFT model was carried out. The study was based on an experiment using a z-string version of the so-called Potsdam Sentence Corpus (PSC) as an oculomotor control condition to normal reading of the PSC. The PSC consists of 144 sentences comprising altogether 1138 words. Forty-six university students (31 women and 14 men, 1 n.a.; mean age = 22.5 years, SD = 2.5 years) scanned the 144 z-transformed sentences. For 26 participants, normal reading PSC data were available; these participants attended two sessions at different days while session order (z-string scanning versus normal reading of the PSC) was randomized.<sup>5</sup> Participants were instructed to pretend that they were reading each line of z-strings (cf., Vitu et al., 1995). The z-string trials were randomly mixed with 36 normal sentences. This was done to encourage a transfer of reading-like behavior (see Nuthmann et al., 2007, for discussion). Participants were tested with a SR Research EyeLink II System with a sampling rate of 500 Hz. Further details of materials, experimental procedure, and data selection are described in Kliegl, Grabner, Rolfs, and Engbert (2004).

## 3. The SWIFT model: Modeling results

For the interpretation of SWIFT's activation-field dynamics, it is important to note that, in the case of reading, we denote activations as a combined variable representing lexical and oculomotor processing of words. When scanning z-strings, there is no lexical processing involved, but there is visual-perceptual and oculomotor-related processing. Within the framework of the present simulations, we therefore understand the activations of z-strings as reflecting ongoing visual-perceptual and oculomotor processing.

In this section, we first discuss the estimation of model parameters and the obtained numerical values (Section 3.1). Second, we evaluate the model's performance by comparing simulated data with empirical results (Section 3.2). Finally, we investigate in detail—on the basis of changes in model parameters—how the

<sup>5</sup> Based on the data from these 26 participants, results for the fixation-duration IOVP effect, landing position distributions as well as fixation duration and saccade length distributions have been reported elsewhere (Nuthmann et al., 2007).

characteristics of eye-movement behavior in z-string scanning map onto the theoretical assumptions underlying the SWIFT model (Section 3.3).

### 3.1. Simulations and model parameters

All simulations reported here were based on the SWIFT model specification for normal reading (Engbert et al., 2005). Thus, we analyze model generalizability of SWIFT in the restricted sense of parameter changes. Note that this is a much more stringent test than adding new parameters to the model. In the following, the new version of SWIFT for the simulation of z-string scanning will be labeled zSWIFT, to distinguish it from the version for normal reading. Table 1 provides an overview of model parameters; to facilitate comparisons, parameter estimates for normal reading data, taken from Engbert et al. (2005), are additionally presented. The nature of the z-string scanning task called for a few adjustments. Given that there is no lexical processing involved when scanning z-strings, two lexical parameters ( $\beta$  and  $\theta$ ) were set to zero (Table 1). First, the maximum activation  $L_n$  of a given z-string is not modulated by word frequency ( $\beta = 0$ ). Second, the (word) processing rate is not modulated by word predictability ( $\theta = 0$ ). In addition, the global decay parameter  $\omega$  (cf., Eq. (5)) which was a fixed parameter in Engbert et al. (2005) is now a free parameter. The decay parameter affects the model's regression behavior. Regression probability is considerably reduced when scanning z-strings. Therefore, we estimated  $\omega$  as a free parameter (cf., Section 1.4.3). Given these adjustments, zSWIFT has 12 free parameter compared to 13 in SWIFT.

Furthermore, several parameters characterising oculomotor behavior were estimated from the empirical data. We assume that saccade targeting is word-based while being subject to a systematic and a random error component (see Sections 1.3.6 and 3.2.5 for in-depth discussion). The parameters of the systematic error component were estimated separately for different types of saccades (Table 2). The results indicate that the parameters are very similar for forward saccades and forward refixations. Typically, z-string scanning data show a small proportion of regressive saccades only. Therefore, for regressive refixations no reliable parameters could be estimated from the empirical data. For the SWIFT model simulations, parameters obtained for forward refixations were adopted for both forward and regressive refixations. For inter-word regressions, no systematic relationship between launch site and mean landing site could be established. As for the random component for the simulation of oculomotor errors, parameters  $\delta_0$  and  $\delta_1$  were estimated across all saccade types (Table 2).

For optimization of parameters, a genetic algorithm was used (for details see Engbert et al., 2002, 2005). The optimization procedure converged, yielding the set of parameters listed in Table 1. There are four major differences in parameter estimations for zSWIFT as compared to SWIFT. First, the visual span is broader when scanning z-strings as compared to reading words. In addition, the attention-based asymmetry disappeared (see Fig. 1). Second, there is a greater inhibition factor for zSWIFT. Third, z-strings are associated with a stronger global decay process, Eq. (5), which translates into a faster decay of activation for z-strings compared with words. Fourth, the word length exponent  $\eta$ , modulating the processing rate of strings, Eq. (4), is greater (and closer to 1) for z-strings as opposed to words.

Interestingly, the present simulations also yielded two notable similarities for simulated z-strings and words. First, the value for  $\alpha$ , the intercept of the word difficulty or lexical access time (see Eq. (1) in Engbert et al., 2005), turned out to be almost identical for z-strings as opposed to words (65.0 versus 63.5, Table 1). Second, when comparing zSWIFT and SWIFT, it turns out that the random timer,  $t_{sac}$ , is set to a similar mean value while the estimations

reported here produced somewhat longer mean durations for the labile and nonlabile stages of saccade programming for z-string scanning as opposed to normal reading (Table 1). Finally, as far as the fixed oculomotor parameters are concerned, it is important to note that empirically investigated differences between z-string scanning and normal reading data are small (Table 2). In particular, for regressions back to a previously encountered z-string or word we observe no systematic relationship between launch site and mean landing site (see also Radach & McConkie, 1998, for normal reading).

### 3.2. Model performance

Simulated data were obtained from 200 runs of the SWIFT model, i.e., the 144 z-transformed PSC sentences were read by 200 virtual participants each. The performance of the model is first evaluated by word-based summary statistics (Sections 3.2.2 and 3.2.3), followed by more detailed analyses of regression patterns (Section 3.2.4). Next, we will take a closer look at phenomena related to the landing position within a string, i.e., the landing position function (Section 3.2.5), the refixation Optimal Viewing Position effect (Section 3.2.6) as well as the IOVP effect for fixation durations (Section 3.2.7).

#### 3.2.1. Simulation example

Fig. 2 visualizes a simulation run of the SWIFT model. The set of activations  $a_n(t)$  dynamically changes over time and is strongly affected by the current fixation position  $k(t)$ . In the example, the sequence of fixated z-strings is 1, 2, 3, 5, 5, 6, 7, 9, 8, 9.

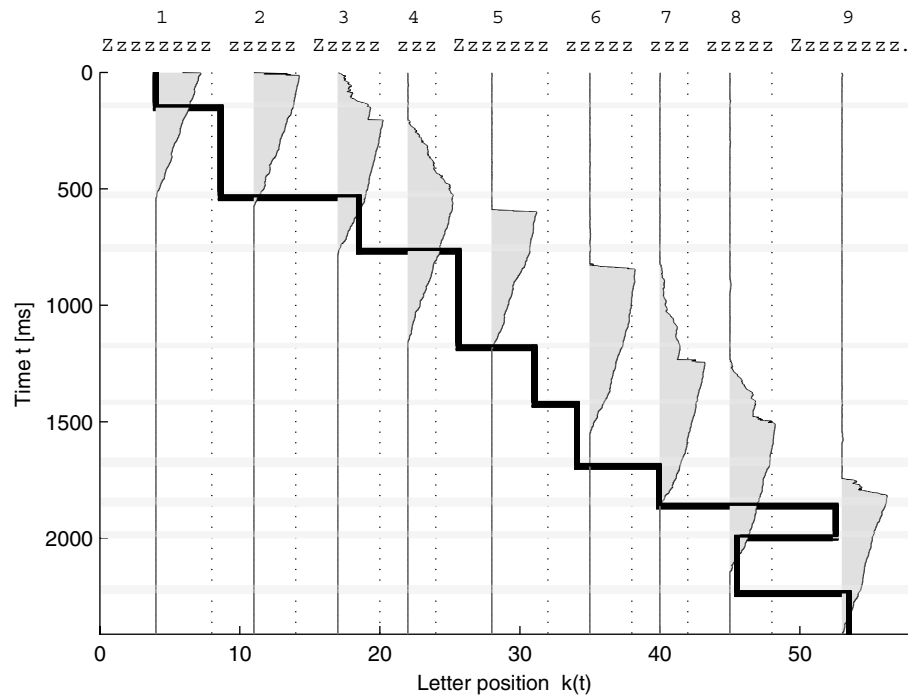
The example illustrates different saccade types encountered in both scanning and reading. Most of the time, the eyes proceed from one z-string to the next. However, in the example the 3-letter z-string 4 is skipped over. At a given time point of saccade target selection, we will usually observe parallel activation of several strings. Skipping is thus a consequence of competing activation among strings for target selection. The fixation data for z-string Nr. 5 represent another type of saccades, i.e., a refixation. The first fixation on the string is at a position close to the beginning of the string. The center of the string is considered to be an optimal position for fixation. Here, the first fixation is rather far away from the center of the string. Therefore, the activation of string 5 is still very high when the next saccade target is computed. Therefore, string 5 wins target selection and is thus refixated. Due to oculomotor error, the second fixation is located towards the end of the string. Finally, z-string 8 is initially skipped, but we observe an immediate regression from z-string 9 back to string 8.

Model performance of zSWIFT can be evaluated by investigating the effect of string length as an independent variable on fixation durations (temporal measures) and fixation probabilities (spatial measures). Temporal measures are on-line indicators of processing load while spatial measures like fixation position and saccade amplitude indicate the direction and sequence of processing (Radach & Kennedy, 2004). At the level of global analyses, the empirical data can be described as follows: Average fixation durations were significantly longer ( $M = 256$  ms versus  $M = 202$  ms) in z-string than in normal reading. The mean length of forward saccades did not differ between the two conditions ( $M = 7.3$  char ms versus  $M = 7.2$  char). However, an evaluation of saccade length distribution indicated that the proportion of short forward saccades (1–5 letters) as well as very long forward saccades ( $\geq 15$  letters) was higher when scanning z-strings than when reading normal sentences; the opposite was true for medium-long saccades (see Nuthmann et al., 2007).

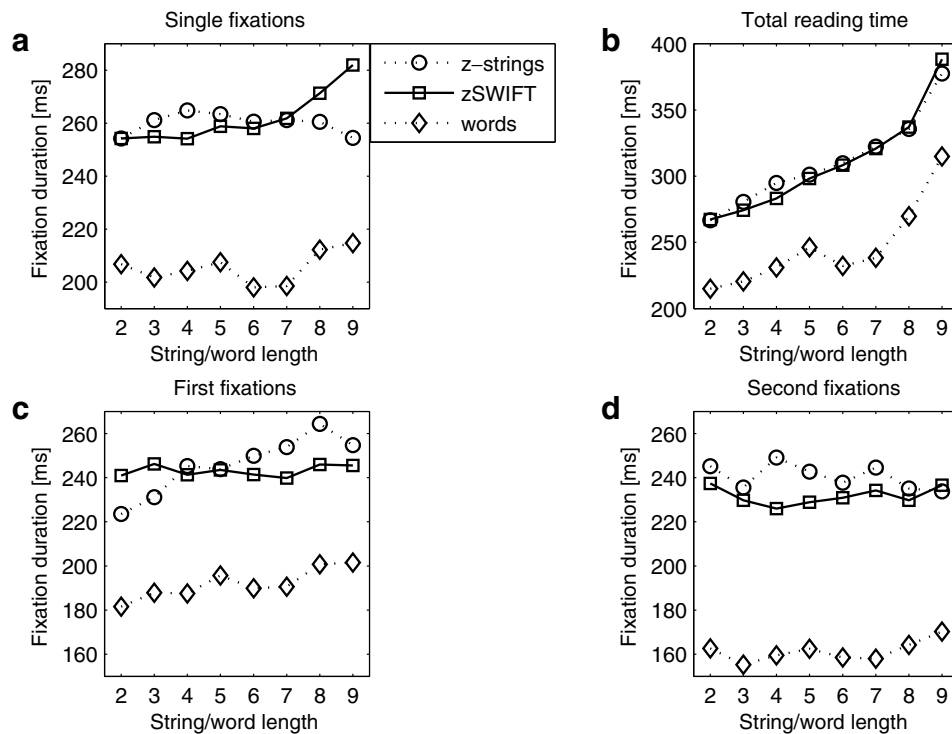
#### 3.2.2. Fixation durations

Single fixation duration represents the ideal case that a given word could be processed with exactly one fixation. For words that





**Fig. 2.** Example of a numerical simulation with the zSWIFT model. Time evolves along the y axis. The dark black line indicates the fixation position  $k(t)$  in units of letters. The gray areas visualize the activations  $a_n(t)$ , whereas the lighter horizontal lines indicate saccades.

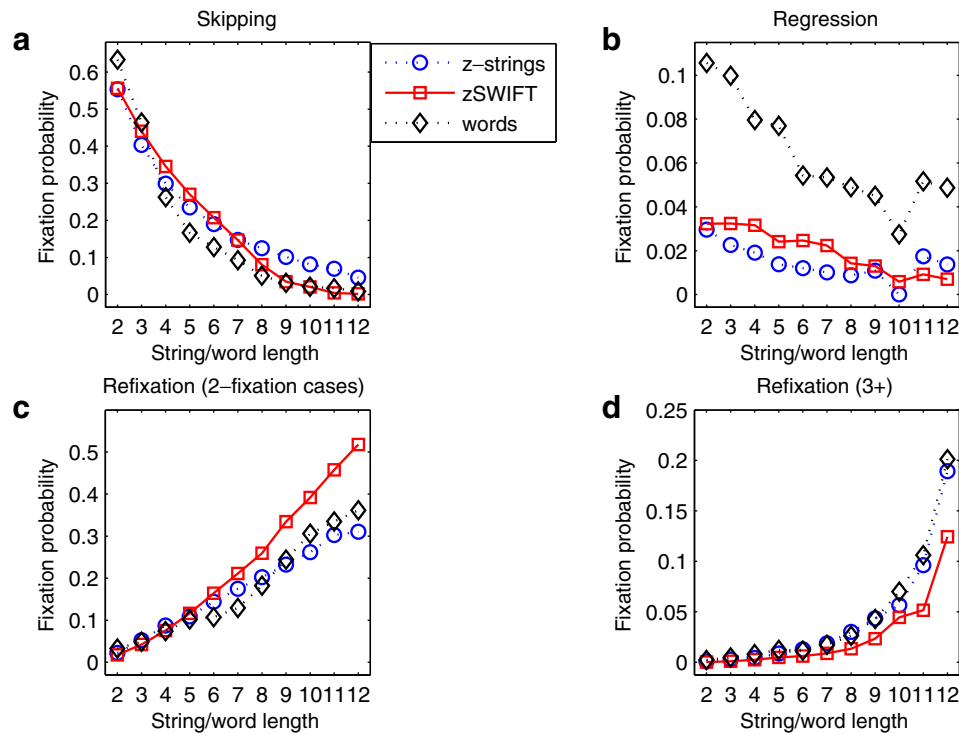


**Fig. 3.** Word-based summary statistics of four fixation duration measures for simulated versus empirical z-string scanning data. For comparison, empirical normal reading data are additionally presented. Mean durations for single fixations (a) and total reading time (b) as well as first (c), and second (d) fixation duration are displayed as a function of word/string length. Results for simulated z-string scanning data (zSWIFT) are represented by squares connected with solid lines.

are fixated at least twice before the eyes leave the word we compute *first* and *second fixation duration*. These three duration measures are computed for first-pass reading, with first pass referring to the initial encounter (or pass) of a word. To take into account that some words are read during more than one pass

through the text, we compute *total reading time* as the summed duration of all fixations made on a given word.

First, fixation durations are globally inflated in z-string scanning, and this is reproduced by the model simulations. Second, like words (diamonds), z-strings (circles) generate effects of string



**Fig. 4.** Word-based summary statistics of four fixation probability measures for simulated versus empirical z-string scanning data. For comparison, empirical normal reading data are additionally presented. Probabilities are displayed as a function of word/string length. (a) Mean probabilities for skipping, (b) the probability that a given word is the target of a regression, (c) probabilities of making two successive fixations, or (d) three or more successive fixations on a word or string. Results for simulated z-string scanning data (zSWIFT) are represented by squares connected with solid lines.

length on fixation durations (Fig. 3). Effects are strong for total reading time and moderate for first fixation and single fixation durations. These string length effects are qualitatively reproduced by the SWIFT model (squares, connected with solid line). The model also does a very good job for total reading time (Fig. 3b), provides reasonable results for single fixation durations (except for word length >8, Fig. 3a), while results for first and second fixation durations, reflecting the model's refixation behavior, are less accurate.

### 3.2.3. Fixation probabilities

Based on first-pass reading, the probabilities of skipping ( $p_0$ ) a string, fixating it twice ( $p_2$ ), and three or more times ( $p_{3+}$ ) can be computed. The probability of a single fixation ( $p_1$ ) is redundant; because the total fixation probability sums to one,  $p_1$  can be calculated from the other probabilities. As a re-reading measure we compute regression probability ( $p_{reg}$ ), i.e. the probability of a word/z-string being the target of an inter-word regressive saccade.

For empirical data, all four fixation probability measures show a string-length effect (Fig. 4), both for z-string sentences (circles) as well as for normal sentences (diamonds). Most notably, short words and/or z-strings are skipped more frequently (Fig. 4a) and receive fewer immediate refixations (Fig. 4c and d). The characteristic patterns for z-string scanning data are qualitatively reproduced by the simulations with the SWIFT model (squares, connected with solid lines). As for refixation probabilities ( $p_2$ ,  $p_{3+}$ ), the model performed well for refixations on short words, but for long words the values for  $p_2$  are too high, while they are underestimated for  $p_{3+}$ , i.e., the model generates too many 2-fixation cases (Fig. 4c) and too few multiple fixation cases (Fig. 4d). The model produces reasonable results for regression probabilities while the overall regression probability appears to be overestimated. Note that z-string scanning elicits considerably fewer regressive saccades as compared to normal reading. Finally, differ-

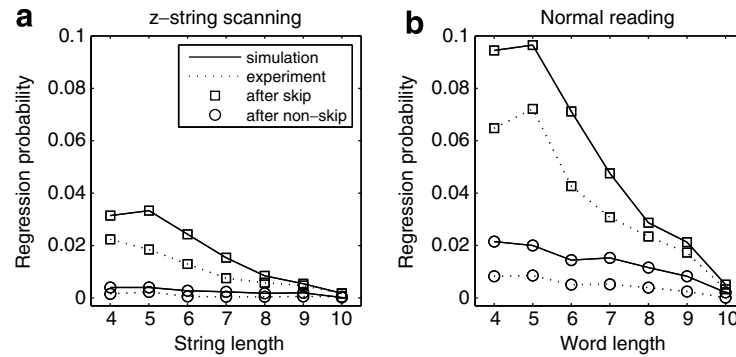
ences in mean saccade lengths between the two tasks translate into a task  $\times$  object length interaction for skipping probabilities (Fig. 4a): In comparison to normal reading, z-strings show a lower skipping probability for very short strings, but a higher skipping probability for long strings (see also Vitu et al., 1995). The model captures the skipping probabilities quite well, except for the very long strings.

### 3.2.4. Patterns of regressions

Earlier analyses of PSC reading data had revealed that regression probability decreases with word length (Kliegl et al., 2004; see also Fig. 4b). Moreover, regression likelihood depends on whether or not a word was skipped during the prior saccade: It is higher in word-skip than in non-word-skip instances (e.g., Engbert et al., 2005; Vitu, McConkie, & Zola, 1998). For the present analyses, we calculated the probability of making a regression back to a z-string of a given length, contingent on whether that string was initially skipped in first-pass reading or not. As a novel finding, Fig. 5a shows that z-string scanning qualitatively shows the same pattern as normal reading (Fig. 5b), yet at a greatly reduced baseline level of regression probability. For example, if a 4-letter z-string was initially skipped, there is a 0.022 probability that the eyes immediately regress back to the string. Notably, this probability is about three times as high for words (Fig. 5b). In addition, regression probability decreases with increasing length of the targeted z-string. If the string was not skipped in first pass, however, the probability that a z-string of a given length is the target of a regression is close to zero. In sum, regressing back to a string after having skipped it during the first encounter appears to be a typical pattern of oculomotor activity.

### 3.2.5. Landing position function

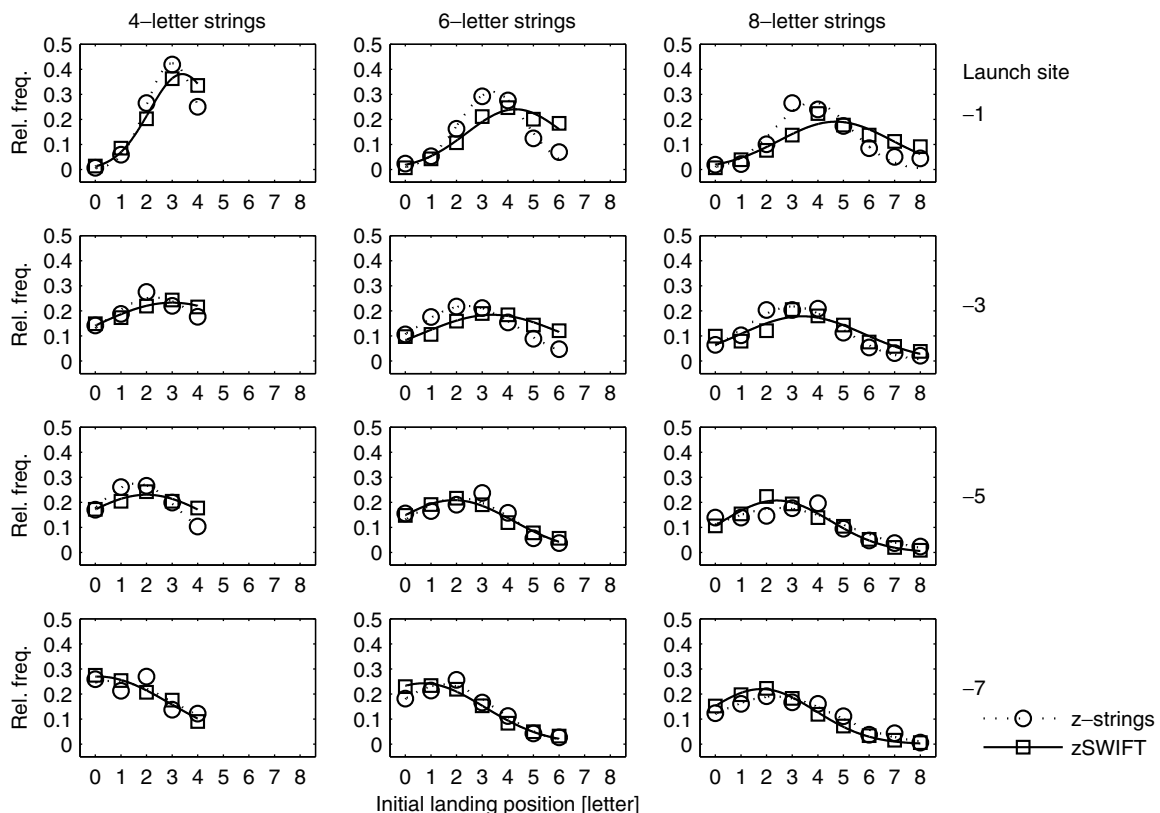
The landing position function refers to where within a letter string people's eyes are located when they read for comprehension



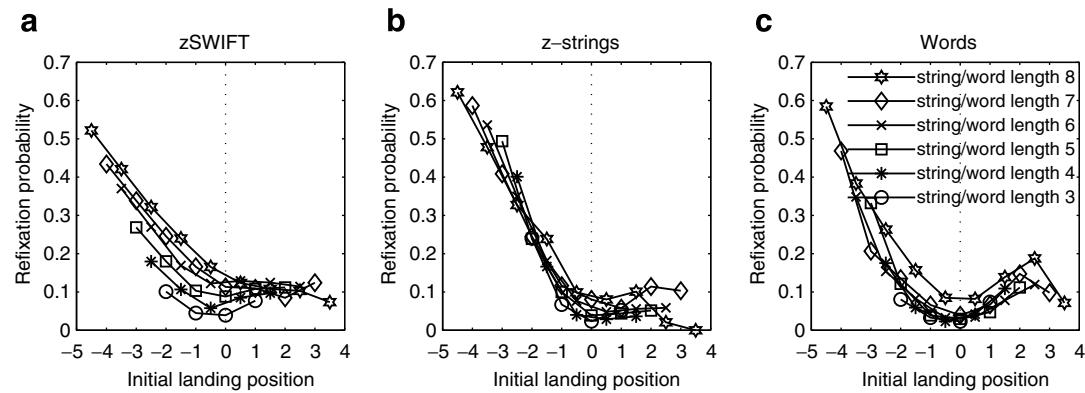
**Fig. 5.** (a) Experimental data (dotted lines) demonstrate that regression probability is higher for z-strings which were skipped in first-pass reading (squares) as opposed to z-strings that were not skipped before being the target of a regression (circles). Moreover, regression probability decreases with increasing string length. Although the qualitative patterns are reproduced by model simulations (solid lines), regression probability is generally higher in simulations than in experimental data. (b) For comparison, empirical and simulated normal reading data from Engbert et al. (2005).

or scan meaningless material. Observed landing position distributions are typically Gaussian in shape and peak around word center or slightly left of it (Preferred Viewing Location, PVL, Rayner, 1979). The PVL (Fig. 6) is modulated by center-based *launch site distance*, that is the distance (in letters) between the launch site of the last saccade and the center of the target word selected for the next saccade (McConkie et al., 1988). The authors identified a systematic and a random component of oculomotor error in saccade targeting. The landing position function (Radach & McConkie, 1998) describes the systematic linear component of oculomotor error with two parameters: its slope as well as the average optimal center-based launch site distance. The slope of the landing position function has been explained in terms of a *saccadic range error* (SRE, cf., McConkie et al., 1988, but see Vitu, 1991). The slope of the land-

ing position function would thus reflect the strength of the SRE. Let us consider inter-word forward saccades as an example (Table 2). For each one-letter increment in center-based launch site distance, the subsequent landing position within the target z-string moves about 0.37 letters towards the beginning of the z-string ( $\delta_{\text{SYS}} = 0.37$ ; Fig. 6). In addition, the mean of the landing position distribution is accurate (i.e., it equals the center of the target string) when the launch site is about 4.45 letters to the left of the center of the target. This is the average optimal center-based launch site distance (across different string lengths); for saccades coming from this region, undershoots and overshoots are balanced. Based on its implementation of oculomotor errors (see Sections 1.3.6 and 3.1), the SWIFT model reproduces the launch-site-contingent landing position distributions very well (Fig. 6). For the closest



**Fig. 6.** Landing position distributions for different string lengths and launch site distances. Comparison of simulated (squares) versus empirical (circles) z-string scanning data. Letter 0 corresponds to the space to the left of the string. Also presented is the best-fitting normal curve for each distribution. Rel. freq.= relative frequency.



**Fig. 7.** Mean refixation probability as a function of the initial landing position within a string/word, for 3- to 8-letter z-strings and/or words. (a) simulated z-string scanning data, (b) empirical z-string scanning data, (c) empirical normal reading data. The initial landing position within a z-string is plotted as letter position relative to the center of the string; 0 and the dotted vertical line represent the center of the string. For z-strings of a given length, the leftmost position corresponds to the space to the left of the string.

launch site right in front of the z-string (−1), the simulated overshoot turned out to be a bit too strong.

As a variable, initial landing position gives rise to the *u*-shaped refixation OVP effect as well as to the IOVP effect for fixation durations.

### 3.2.6. Refixation probability OVP effect

There is a widely accepted view that a typical reading saccade targets the center of a selected target word as its optimal viewing position (see Section 1.3.5). One piece of evidence for this notion is provided by refixation probability curves. The refixation probability OVP effect refers to the observation that refixation probability (i.e., the likelihood of making more than one fixation on a word before moving to another word) is lower when the eyes initially fixate the middle of the word than when they initially fixate one of the word's ends (e.g., McConkie et al., 1989; Nuthmann et al., 2005; Rayner et al., 1996; Vitu et al., 2001). The fact that refixation probability is minimal around word center is a piece of evidence for considering word center as the optimal viewing position in continuous reading. Typically, the *u*-shaped refixation probability curves are asymmetrical: Refixation probability is higher when the fixation falls on the beginning than on the end of the word. This asymmetry is even more pronounced for z-string scanning (Fig. 7b; see also Nazir, 1991) as compared to normal reading (Fig. 7c).

In SWIFT, refixations on long words are generated because of visual acuity limitations, which are incorporated by the assumption of a processing gradient. Refixations on short words mainly occur as a consequence of autonomous saccade timing and stochastic target selection. In sum, these mechanisms allow to reproduce the empirical refixation data reasonably well; both the quadratic form of within-word refixation probabilities (Fig. 7) as well as mean word-based refixation probabilities as a function of word length (Fig. 4) are accounted for. Yet the SWIFT model is certainly somewhat underspecified in that it does not account for all factors that influence refixation behavior. It is, however, currently the only computational model where the initiation of refixation saccades is an inherent consequence of the model architecture. In contrast, the E-Z Reader model incorporates two extra parameters to account for the typical *u*-shaped refixation probability curve. In particular, a refixation program is initiated with a probability that is a function of the absolute distance between the initial landing position on a word and the words optimal viewing position (Pollatsek et al., 2006). In the SERIF model, the *u*-shaped refixation probability curve serves as input for modeling the metrics of refixations: Refixation saccades are generated according to a random process, sampling from empirically determined quadratic refixation probability functions (McDonald et al., 2005).

Finally, McConkie et al. (1989) raised the fundamental question: “Why is it that high-frequency, four-letter words are ever refixed, and more particularly, why are they sometimes refixed following an initial eye fixation at their center” (p. 252)? The authors reasoned that the refixation probability minimum for short, high-frequency words<sup>6</sup> indicates the frequency of refixations that occur for reasons other than word recognition failure due to insufficient visual information. The SWIFT model provides an explanation for this subpopulation of refixation saccades: They are a consequence of autonomous saccade timing and stochastic target selection.

### 3.2.7. IOVP effect for fixation durations

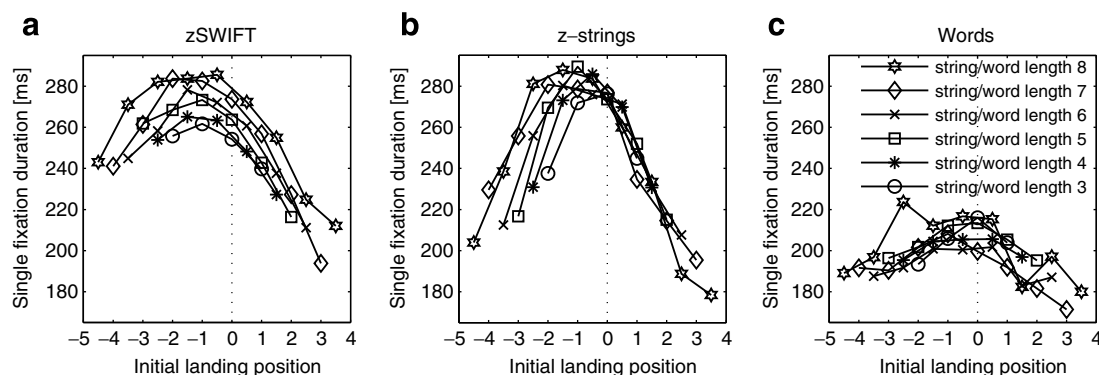
According to the refixation OVP effect, one would expect that not only refixation probabilities but also fixation durations would be lowest when the eyes are located close to word center. However, empirical reading data are suggestive of an *Inverted-OVP* effect with fixation durations actually being longest rather than shortest at word center (McDonald et al., 2005; Nuthmann et al., 2005; Vitu et al., 2001; White & Liversedge, 2006). Recently, we argued that the IOVP effect may arise as a consequence of mislocated fixations, if we assume that (1) a new saccade program is immediately started whenever an intended word is missed and that (2) mislocated fixation locations are more likely to be found at the beginnings and ends of words. This explanation relies on low-level perceptual-oculomotor mechanisms unrelated to word recognition and was implemented and validated with the SWIFT model (Engbert et al., 2005, 2007). IOVP effects also emerge in z-string scanning, with an even stronger curvature than in normal reading (Fig. 8; see also Nuthmann et al., 2007). IOVP effects in z-string scanning, conceptualized as an oculomotor control condition to normal reading, are compatible with the mislocation hypothesis (for a discussion of alternative explanations see Nuthmann et al., 2007). In recent work, we showed that our proposed IOVP model qualitatively reproduced the strong IOVP effect in z-string scanning (Nuthmann et al., 2007). With the present work, it is demonstrated that the SWIFT model is also capable of reproducing the strong IOVP effect in z-string scanning, as demonstrated in Fig. 8 for single fixation durations.

### 3.3. Discussion

In the previous sections, it was shown that the SWIFT model can reproduce a large number of experimental findings obtained with

<sup>6</sup> Note that we typically observe a substantial negative correlation between word length and frequency (e.g., Kliegl et al., 2006).





**Fig. 8.** Inverted-Optimal Viewing Position effects for single fixation durations as a function of string and/or word length for simulated (a) versus empirical (b) z-string scanning data, compared to empirical normal reading data (c).

the z-string scanning paradigm. In the present section, we will now discuss how the empirical differences in eye-movement behavior observed when scanning sentences consisting of z-strings as opposed to reading of meaningful sentences are related to differences in model parameter estimates for the two conditions.

### 3.3.1. Prolonged fixation durations

One of the key findings of empirical studies is that fixation durations are longer (rather than shorter) in z-string scanning as compared to normal reading. The present simulations suggested a broader processing span when scanning meaningless material as opposed to reading (Table 1). Interestingly, zSWIFT's random timer is set to a similar mean value as in normal reading. Note that the initiation of a new saccade program is delayed by an inhibition process which, on average, leads to increased fixation durations. This inhibition process is enhanced in case of a broader processing span: Due to a normalization of the total processing rate (Engbert et al., 2005), a broader span leads to slower local processing rates.<sup>7</sup> Therefore, a key result from our simulations is that zSWIFT provides a new explanation for the observed increased average fixation duration in scanning compared to reading.

### 3.3.2. String length effects

In the SWIFT model for normal reading, the maximum of a word's activation is determined by word frequency (see Eq. 1 in Engbert et al., 2005). Z-string scanning approximates reading without lexical processing. Consequently, in zSWIFT the activation maximum is not modulated by frequency and is thus the same for all z-strings (see also Fig. 2). However, we formulated assumptions on visual processing which determine how the length of a word or z-string affects its processing rate, Eq. (4). More specifically, in the simulations of the z-string scanning data, the word length component  $\eta$  turned out to be closer to one than in normal reading (Table 1), which translates into a more substantial processing advantage for short strings.

### 3.3.3. Reduced regression probabilities

In the SWIFT model, regressions are triggered by incomplete processing. In particular, a regressive or left-directed saccade is executed when a word/string to the left of the current fixation point is selected as a saccade target from all currently activated words, because this word still shows significant activation and thus processing needs. According to our simulations, z-strings are associated with a stronger global decay process which translates into a faster decay of activation

for z-strings compared to words. This in turn leads to a reduced regression probability. We interpret the increased global decay as a consequence of the absence of word recognition: In zSWIFT, activations have the single purpose of computing saccade targets.

At a given point of saccade target selection, we will typically observe parallel activation of several strings or words (cf., Fig. 2). The activations represent a measure for target selection probability. The present simulations suggested a broader processing span for z-string scanning than for normal reading (Fig. 1), which essentially leads to longer fixation durations. A larger right-extension of the span in z-string scanning as compared to normal reading results into more parafoveal preprocessing, and this contributes to higher simulated skipping probabilities, especially for medium-length z-strings (Fig. 4a).

## 4. General discussion

Eye movements in reading are affected both by low-level oculomotor mechanisms as well as moment-to-moment cognitive processes. The two types of influences can be contrasted with the mindless reading paradigm. Participants are asked to scan a given text in a version where words are transformed into z-strings. These data are compared with a control condition where participants read the normal mindful version of the text. Assuming that z-string scanning approximates reading without word recognition or higher-level language processing, the mindless reading condition constitutes an oculomotor control condition to normal reading. The goal of the present work was to model z-string scanning data with the SWIFT model of saccade generation (Engbert et al., 2005), for several reasons. First, the simulations were performed to analyze the generalizability of SWIFT, a cognitive model incorporating oculomotor elements, to a scanning task. From our perspective, model generalizability is an important question for the development of theoretical models of eye-movement control. In particular, the present simulations represent an important test of the psychological plausibility of the SWIFT model's assumptions on visuomotor processing, saccade generation as well as the concept of a dynamically changing activation field for movement planning. Second, the zSWIFT simulations provide theoretical explanations for key findings obtained from the z-string scanning paradigm.

Most of all, why are fixation durations prolonged even though there is nothing meaningful to process? This seemingly contrainuitive finding has led researchers to suggest that participants "do something odd" when performing the task. First, it has been argued that, when asked to mimic reading, participants simply overestimate the time they spend at each fixation during normal reading (e.g., Vitu et al., 1995). However, participants are generally unaware of saccades, and we would thus suspect that they are unable

<sup>7</sup> Apart from that, simulations also yielded a higher numerical value for the inhibition factor  $h$  (Table 1). However, as detailed in Section 1.4.1, the specific values of  $h$  do not allow for a psychological interpretation.

to consciously influence their eye movements in a scanning task.<sup>8</sup> Current criticism seems to target the instruction given to the participants. Typically, participants are asked to scan the text as if they were reading (Nuthmann et al., 2007; Rayner & Fischer, 1996; Vitu et al., 1995). In a x-string scanning condition of a recent study, however, a modified instruction was used: Participants were told to scan along the horizontal array of Xs (Liversedge et al., 2004). The authors emphasize that total sentence reading times are shorter for the mindless arrays of Xs than for the meaningful sentences. However, their fixation duration data actually suggest increased durations for the x-string scanning condition as compared to normal reading<sup>9</sup>, which is in agreement with the other scanning studies. This indicates that differences in instruction alone cannot account for prolonged fixation durations in continuous z-string scanning, yet further systematic experimentation is needed to substantiate this claim. We note that prolonged fixations are quite a consistent finding. An analysis of individual differences showed that only two participants showed slightly shorter fixation durations in z-string scanning as opposed to normal reading (unpublished data). Inflated fixation durations were also observed in a recent study, where we investigated eye-movement control during reading of sentences with randomly shuffled words (Schad, Nuthmann, & Engbert, submitted for publication). This is a further control condition to normal reading, where lexical processing of single words is maintained but syntactic or semantic integration processes are (largely) excluded.

If we accept that z-string scanning is a good enough approximation of reading without higher-level language processing, simulating such data with a theoretical model makes a valuable contribution to resolving the mystery of prolonged fixation durations and might help to direct future empirical research. With the present modeling work based on SWIFT, we offer an alternative explanation for the inflated fixation durations in z-string scanning. In SWIFT, the cognitive control of fixation durations is implemented by foveal inhibition. Because simulations with the SWIFT model suggest a broader perceptual span when scanning z-string sentences as opposed to reading meaningful sentences, the average word-based activations are higher in the z-string condition. As a consequence of higher activations, foveal inhibition is increased, which produces higher average fixation durations. Thus, the cognitive architecture of the SWIFT model provides a psychological explanation for why average fixation durations in different oculomotor paradigms are longer than in reading (see also Trukenbrod & Engbert, 2007, for visual search).

We would like to comment on one particular result of the parameter estimations for zSWIFT. The simulations suggested a somewhat broader perceptual span in z-string scanning than in normal reading. Further, the span turned out to be symmetric around the current point of fixation (see Fig. 1), suggesting that the asymmetric attention-based perceptual span observed in normal reading turns into a symmetric visual span when scanning meaningless z-strings. Thus, it might not be the reading direction but the serial-directive nature of letter processing that drives the asymmetry observed in normal reading.<sup>10</sup> Currently, there are no empirical data on the perceptual span in z-string scanning available. Generally, the relative contributions and interactions of visual and attentional components to the perceptual span in reading are still an open empirical research question. Here, empirical and computational research can be mutually enriching. On the one hand, zSWIFT makes predictions that could be validated experimentally

by employing the moving-window paradigm (McConkie & Rayner, 1975). On the other hand, empirical research might lead to refinements in the theoretical model.

Empirical data in both reading and scanning show that the length of a word or string affects measures of fixation durations and fixation probabilities. For example, as string length increases, total reading time increases and skipping probability decreases. SWIFT reproduced these effects not only for words (Engbert et al., 2005) but also for z-strings. In the SWIFT model, there is no direct implementation of word length effects. Rather, they are the consequence of assumptions on visual processing. In SWIFT, a word's frequency modulates the maximum activation of that word. Furthermore, processing difficulty, as reflected by word frequency, can inhibit the initiation of a new saccade program. One could therefore argue that word length effects can be introduced via the correlation between word length and frequency. However, in z-string scanning the notion of word frequency becomes obsolete. In zSWIFT, string-length effects are thus not mediated by word frequency. They are the consequence of a Gaussian-type distribution of processing rate around the current fixation position. Consequently, the fact that we successfully modeled string-length effects in a scanning paradigm lends support to SWIFT's assumptions on visual processing.

Interestingly, modeling regression patterns in z-string scanning with the SWIFT model allows us to test whether the concept of an evolving field of activations for saccade preparation is computationally adequate and psychologically plausible. In SWIFT we propose one common mechanism underlying all types of saccades; this implies that we do not make specific assumptions about regressions or refixations. Both inter- and intra-word regressions depend on ongoing processing (word identification processes in reading) in the same manner as inter- and intra-word progressive saccades. The line of text is seen as a saliency map while the saliency of words is a function of their activation level. Regressive saccades occur when a word to the left of the current fixation point requires further processing. zSWIFT qualitatively reproduced not only regression and refixation probabilities as a function of string length (Fig. 4), but also specific regression patterns. Empirical reading data suggest that inter-word regressions are more likely when the prior saccade skips over a word while regression probability is further modulated by the length of the skipped word as well as its frequency (Vitu et al., 1998). Here we investigated whether z-strings of a given length were targeted by a regression while taking the skipping status of the string into account. The z-string data showed the same characteristic pattern as normal reading data, yet at a considerably reduced baseline level of regression probability (Fig. 5). The empirical data patterns were qualitatively reproduced by the zSWIFT model. In sum, the simulation results lend support to the SWIFT hypothesis that at least short-range regressions, in contrast to so-called long-range regressions (e.g., Weger & Inhoff, 2007), are due to incomplete processing (cf., Vitu, 2005 for a discussion of hypotheses to account for regressions in reading). Taken together, we would argue that the present simulations provide support for the concept of saccade target selection being tied to a dynamically changing field of activations. The fact that regression probabilities are systematically overestimated in the simulations, however, indicates that more constraints are needed to fully reproduce patterns of regressions.

A viable computational model of eye-movement control in reading must account for the effects of basic visual, oculomotor, and linguistic variables on eye movements. Furthermore, it should be able to reproduce differences between groups of readers (see Laubrock, Kliegl, & Engbert, 2006 for applying SWIFT to age differences in reading), as well as differences induced by experimental manipulations. There has never been evolutionary pressure to optimize reading abilities (i.e., humans did not specially adapt to

<sup>8</sup> It appears that participants have little knowledge about their eye-movement behavior, i.e., the locus of attention is more reliable than gaze position (Deubel & Schneider, 1996).

<sup>9</sup> No statistics were reported.

<sup>10</sup> We thank Ralph Radach for suggesting this interpretation.

reading). Therefore, in visual–cognitive tasks different from reading, many of the involved cognitive and oculomotor subsystems overlap or are even the same. What is unique about reading is that it engages both vision and language. Note, however, that current models of eye-movement control in reading are still underspecified as they only take into account relatively “low-level” aspects of the actual reading process, i.e., up to the level of lexical access. In sum, as a working assumption for a general model of eye-movement control, we assume that there is a common basic architecture which is modulated by task-specific mechanisms. Consequently, plausible models of eye-movement control in reading must have the potential for generalization to nonreading tasks. Here, the z-string scanning task represents a well-structured case requiring eye movements in one dimension only. A priori, the SWIFT model was designed as a *general* model of eye-movement control. With the present work we successfully modeled the z-string scanning data using a new set of model parameters in SWIFT—a result which is particularly important from the perspective of model validation and generalizability. As for model comparisons, we expect that other models of eye-movement control in reading would have to make additional conceptual assumptions to simulate z-string scanning. On the one hand, in the E-Z Reader model (Pollatsek et al., 2006; Reichle et al., 1998, 2003) the oculomotor system starts to program a saccade to the next word as soon as a first stage of lexical processing is completed. Thus, the decisions about when to move the eyes are inseparably tied to word recognition, which is absent in z-string scanning. Furthermore, additional assumptions are made with respect to refixations (Pollatsek et al., 2006) while, in its current implementation, E-Z Reader cannot handle regressions. In sum, a full account of z-string scanning might turn out to be difficult to achieve in the E-Z Reader framework. On the other hand, the SERIF model (McDonald et al., 2005) simulates saccade latencies as a race between two hemispheric rise-to-threshold saccadic decision units. Thus, intersaccadic intervals are controlled via linear rises of activation in response to incoming information. In principle, such a model is able to simulate z-string scanning data.<sup>11</sup> However, in SERIF saccade targeting is implemented via explicit parameter fitting in contrast to process assumptions in SWIFT and E-Z Reader. Consequently, there would be limited new psychological insight from SERIF simulations of eye-movements during scanning. Moreover, the architecture of SERIF does not allow to reproduce the strong IOVP effect observed in z-string scanning (Nuthmann et al., 2007).

Even though the z-string scanning paradigm has been termed mindless reading, it does not really capture the phenomenon of mind-wandering in reading, i.e., the experience of having our eyes move across the text while our mind is elsewhere.<sup>12</sup> In that sense, for a computational model scanning of z-strings might be a better approximation of mindless reading than for human beings.

The mindless reading paradigm was originally developed to investigate the extent to which eye-movement behavior is affected by low-level oculomotor factors versus higher-level cognitive processes (Vitu et al., 1995). The focus of the current paper was clearly on computational modeling of the z-string data and not so much on a comparison of normal, mindful as opposed to mindless reading data. Nevertheless, two findings shall be highlighted. First, the probability of inter-word and intra-word regressions is considerably reduced in z-string scanning, suggesting that a substantial proportion of regressive saccades is related to lexical processing or to higher-level word integration processes. Second, previous

studies have been reported that overall landing position distributions are very similar in z-string reading as compared to normal reading (Nuthmann et al., 2007; Rayner & Fischer, 1996; Vitu et al., 1995). The present data allowed a more detailed investigation of the parameters of the landing position function for different types of saccades. A comparison of parameters for z-string scanning versus normal reading suggests that differences in parameters for forward inter-word saccades as well as forward refixations are small (Table 2). These similarities for both conditions suggest that where the eyes land within a word is not so much influenced by ongoing linguistic processing (but see White & Liversedge, 2006 for subtle linguistic influences on the eyes' landing positions during reading). Yet, results on the landing position function also suggest that readers do not give up on their object-based saccade targeting strategy when asked to scan meaningless z-strings.

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<sup>11</sup> See the project home page [http://www.iccs.inf.ed.ac.uk/~smcdonal/Wellcome/model\\_demo.html](http://www.iccs.inf.ed.ac.uk/~smcdonal/Wellcome/model_demo.html) for example simulations.

<sup>12</sup> A first step in this direction is work by Schooler, Reichle, and Halpern (2004) who used a thought sampling technique to investigate “zoning out” while reading, but no eye movements were recorded.

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